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GRAPH-BASED METHOD FOR MULTITEMPORAL SEGMENTATION OF SEA ICE FLOES FROM SATELLITE DATA

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ABSTRACT:

Automated segmentation of the sea ice evolution would allow scientists studying climate change to build accurate models of the sea ice meltdown process, which is a sensitive climate indicator. In this paper, we propose a novel approach which uses shape analysis and graph-based optimization for segmentation of a multiyear ice floe from time series of satellite images. Differently of the state-of-the-art sea ice segmentation techniques, the new method does not rely on the coherence of the intensity values between successive time moments, but only on the coherence of the shape. We successfully validated the performance of the proposed approach on a set of AMSR-E and MODIS images and estimated the area of a sea ice floe as a function of time.

1 INTRODUCTION

The sea ice cover is both a sensitive climate indicator and an active participant of the Earth's climate system (Le Treut et al., 2007). Therefore, it is very important to monitor the sea ice meltdown process. Satellite-based remote sensors acquire data for the continuous monitoring of ice floes at global scales. There is thus a need to develop methods for automated segmentation of the sea ice evolution.

Most of the state-of-the-art techniques for automatic ice floe segmentation from radar or optical remote sensing data sets use adaptive thresholding for distinguishing ice from water areas (Zhang, 1992, Haverkamp and Tsatsoulis, 1996). Recently, iterative region merging methods were proposed to track ice floe (Yu, 2009, Tarabalka et al., 2012). Even though the partition obtained by applying hierarchical step-wise region merging, such as in (Tarabalka et al., 2012), is optimal regarding the minimization of the internal heterogeneity of regions, this method does not cope well with segmentation of noisy and low-contrast images, where internal heterogeneity of the ice floe intensity can be higher than the intensity difference between floes and a background.

In this paper, we propose a new method for multitemporal segmentation of multiyear ice floes from temporal sequences of satellite images. The method performs hierarchical step-wise optimization to construct an initial graph of connected adjacent image regions, and then seeks for a connected subgraph corresponding to an ice floe region, by minimizing a foreground energy. The advantage of the new method when compared to the previously proposed techniques is that it does not rely on the coherence of the intensity values between successive time moments, but only on the coherence of the shape. It thus succeeds in segmenting images where both foreground and background intensity distributions vary significantly over time.

The rest of the paper is organized as follows. In the next section, the data set used for experiments is described. Section 3 presents the proposed segmentation approach. Experimental results are discussed in Section 4, and conclusions are given in Section 5.

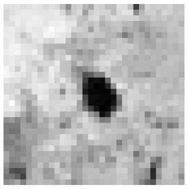
2 DATA SET

We analyzed data from two instruments onboard the NASA Aqua satellite: Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E) and Moderate-Resolution Imaging Spectroradiometer (MODIS). This satellite has a polar orbit enabling several measurements per day over the Earth's polar regions. The objective was to segment a multiyear ice floe, which left the Arctic sea ice pack in December 2007, continuously moved with the Arctic ocean currents and melted in June 2009.

The position of the ice floe of interest was detected by using the AMSR-E data at 89 GHz mapped to a polar stereographic grid at 6.25 km spatial resolution. These data have been extracted from the "AMSR-E/Aqua Daily L3 6.25 km 89 GHz Brightness Temperature Polar Grids" product distributed by the National Snow and Ice Data Center. A multiyear ice has a low microwave emissivity and thus appears dark in AMSR-E images, and in this way distinguishable from clouds and younger ice which has a higher emissivity. However, the low spatial resolution of the AMSR-E data does not allow to accurately segment the ice floes from the background.

In accordance with these tracking measurements, a time series of the AMSR-E and MODIS images was built with the ice floe of interest. We used band 1 (0.620 - 0.670 μm, spatial resolution of 250 m) of the MODIS data, because it has the highest MODIS spatial resolution and provides the best contrast between the sea ice and the ocean water. Level 1B calibrated and geolocated MODIS swath data reprojected onto a polar stereographic grid was the main data source. The geolocation uncertainty is $\sim$50 m (Wolfe and Nishihama, 2009).

All swath images did not provide opportunities to quantify the ice floe areas either due to limited solar illumination, extensive cloud cover, or weakness of contrast between the multiyear ice and the neighboring young ice. We chose for our analysis T = 50 images with spatial dimensions of $H \times W = 800 \times 800$ pixels, acquired on 21 different days during the two-months period from mid-August to mid-October 2008 (from the 227th day to the 286th day of 2008). Figure 1 shows examples of AMSR-E and corresponding MODIS images from the considered set.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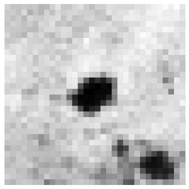
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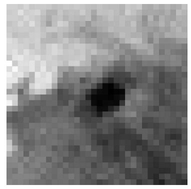
(c)

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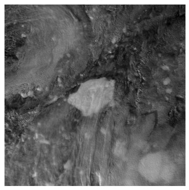
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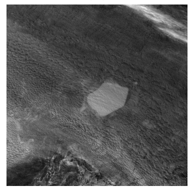

(f)

Figure 1: (a)-(c) MODIS and (d)-(f) AMSR-E images acquired on the 5th, 10th and 19th day, respectively.

3 PROPOSED METHOD

The proposed method belongs to the category of causal, or feed-forward, temporal segmentation techniques (Paris, 2008), which consider only past data for iteratively segmenting each next image. It allows thus to segment ice floes in real-time, given the low acquisition rate. In the following, each step of the proposed iterative technique (each iteration corresponds to one time moment) is described.

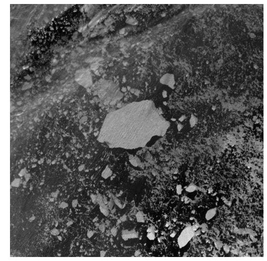
At the input, T 1-band AMSR-E and MODIS images including the ice floe of interest are given. We denote each of the AMSR-E and MODIS images by A_t and I_t, $t = 1, ..., T$, respectively. The goal is to obtain for each time moment t a segmentation map $S_t = \{s_t(x, y) \in [0, 1], x = [1..H], y = [1..W]\}$, where each pixel has label 1 if it belongs to the considered floe, and 0 otherwise.

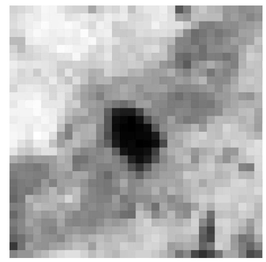
3.1 Floe detection and alignment

First, each AMSR-E image is smoothed by Gaussian lowpass filter ($\sigma = 8$, size = 300×300) and normalized between 0 and 1. The obtained smoothed image is thresholded to detect a multiyear ice floe, yielding a black and white image with a blob-like element corresponding to the floe of interest (see Figure 2(b-c)). Because a multiyear ice has a very low microwave emissivity, we recommend to choose a small positive value of the binary threshold Θ (we used $\Theta = 0.1$ in our experiments). Then, the position (approximate coordinates of the floe center and the rotation angle) of the ice floe is detected, by applying an ellipse fit algorithm on the extracted blob. This position information is used to align each MODIS image with the MODIS image in the preceding time moment from the considered time series. Example of the MODIS image alignment is shown in Figure 2.

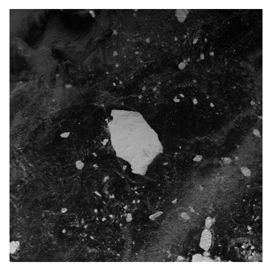
At the next stage, we exhaustively partition each MODIS image into three non-overlapping regions:

1. Floe core, which is a reliable region in the center of the floe.
2. Background mask, which contains reliable background pixels.
3. Working area, which contains both floe and background pixels, including a border of the floe, and which is located between the floe core and the background mask.


(a) MODIS image at the previous time moment $(t-1)$


(b) AMSR-E image at the current time moment t


(c) Detected position of the ice floe (blob-like element)


(d) MODIS image at the time moment t

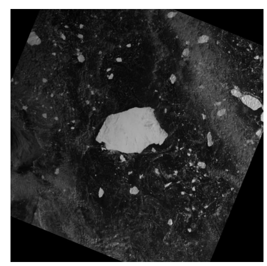

(e) Aligned MODIS image at the time moment t

Figure 2: Floe detection and alignmentt

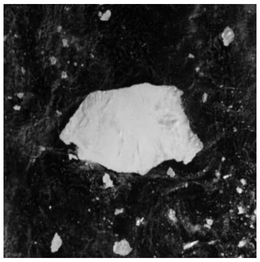
An example of these three regions is shown on Figure 3(b). We detect the floe core (1) by applying an erosion on the AMSR-E-derived blob-like element with the disk structuring element of radius $r = 30$ pixels (Soille, 2003). The background mask (2) is similarly computed by dilating the blob-like element with the disk structuring element of radius $r = 60$ pixels. In the following steps, we seek for a segmentation contour only within the working area.

3.2 Hierarchical step-wise optimization

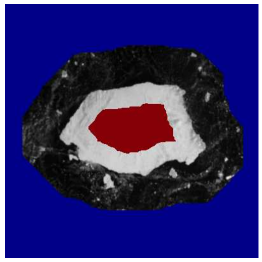
At this step, best merge region growing is performed (Beaulieu and Goldberg, 1989) within the working area of each MODIS image, yielding its exhaustive partitioning into M homogeneous regions, which we call macro-pixels. The algorithm is initialized by assigning a new region label for each pixel of the working area. Then, at each iteration the two most similar spatially adjacent regions are merged, until working area is split into M regions (see Figure 4).

The measure of dissimilarity is computed by using the square root of mean squared error criterion (RMSE), combined with the standard deviation spatial feature (SDSF), as described in (Tilton, 2009). The RMSE between two image regions R_i and R_j, with region intensity means μ_i and μ_j, and region sizes (number of pixels) n_i and n_j, respectively, is defined as:

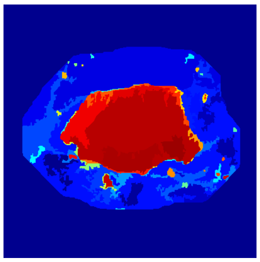
$$RMSE_{ij} = \left[\frac{n_i n_j}{(n_i n_j)} (\mu_i - \mu_j)^2 \right]^{\frac{1}{2}}. \quad (1)$$



(a) Aligned MODIS image



(b) Non-overlapping regions.



(c) Output of hierarchical step-wise optimization ($M = 30$)

Figure 3: MODIS image partitioning

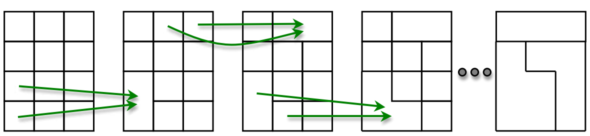


Figure 4: Schematic illustration of a hierarchical step-wise optimization on a set of spatially adjacent image pixels.

The SDSF we used is equal to the mean normalized standard deviation. For regions consisting of two or more pixels, the SDSF of a region R_i with the intensity mean μ_i and region size n_i is computed as:

$$sdsf_i = \sigma_i = \frac{\sqrt{\frac{1}{n_i - 1}\sum_{x_p \in R_i}(x_p - \mu_i)^2}}{\mu_i}. \quad (2)$$

The dissimilarity criterion between each two adjacent regions R_i and R_j is then computed as:

$$DC_{ij} = RMSE_{ij}\left[1.0 + \frac{|sdsf_i - sdsf_j|}{(sdsf_i + sdsf_j)}W\right], \quad (3)$$

where the parameter W sets the importance of taking into account the SDSF. We set $W = 4$ in our experiments.

Figure 3(c) shows an example of the image partitioning into a set of macro-pixels, obtained by applying the hierarchical step-wise optimization step. Once the partitioning is performed, an image graph is built with a set of nodes {floe core, macropixel 1, ..., macropixel M} and edges connecting spatially adjacent nodes. The objective of this step is to reduce the number of nodes in the image graph, resulting in a lower computational time of the overall method. The value of M is set empirically and it should be high enough to avoid undersegmentation. We used $M = 80$ in our experiments.

3.3 Energy minimization on the resulting graph

Finally, we seek for a connected subgraph $S =$ {floe core, {subset of macropixels}} of the constructed image graph, which corresponds to the ice floe region. For this purpose, a foreground energy is defined as a sum of *shape* and *data* terms, which depend on the shape of the considered region and on the gradient at the border of the region, respectively:

$$E = E_{shape} + \alpha E_{data}. \quad (4)$$

The weighting parameter α balances the contribution of these two energy terms. In our experiments we used $\alpha = 0.25$. The shape term for the considered subgraph G_i is computed as the dissimilarity between a shape of the current region (i.e., region corresponding to G_i) and an average shape of the segmentations at k previous time moments, which we denote by G_{pr} (the choice of k depends on the speed of the shape change between consecutive frames; we set $k = 3$):

$$E_{shape_i} = \sum_{\theta=0^\circ}^{360^\circ} diff_{i,\theta}. \quad (5)$$

We use a Manhattan distance between normalized shape profiles as a dissimilarity criterion:

$$diff_i = |d_i(\theta) - d_{pr}(\theta)|, \quad (6)$$

where $d_i(\theta)$ is a distance from the centroid point of the region G_i to the region border at the angle θ. Before applying (6), regions G_i and G_{pr} must be aligned according to their centroid points and major axes. Since θ can take an unlimited amount of values between 0° and 360°, we must set beforehand a $d\theta$ in order to have a sufficient accuracy and a reasonable computational speed for each comparison. In our experiments we used $d\theta = 3^\circ$.

The data term is computed as a normalized gradient sum along the border of the current region. Because we seek to minimize the total energy E, we use the following edge indicator function for each point x of the region border C (Schoenemann and Cremers, 2007):

$$g(x) = \frac{1}{1 + \nabla C(x)} \quad (7)$$

This function is averaged along the curve C, so not to discourage segmentations with longer perimeters:

$$E_{data_i} = \frac{\sum_{p=0}^{l(C_i)} g(C_i(p))}{l(C_i)}. \quad (8)$$

The total energy is thus computed as

$$E_i = \sum_{\theta=0}^{360} diff_{i,\theta} + \alpha\frac{\sum_{p=0}^{l(C_i)} g(C_i(p))}{l(C_i)}. \quad (9)$$

The ice floe region is segmented by finding a connected subgraph S that minimizes the foreground energy.

4 RESULTS AND DISCUSSION

We applied the proposed method to the time series of AMSR-E and MODIS images described in Section 2, and compared results with those obtained by performing hierarchical step-wise optimization (Beaulieu and Goldberg, 1989) to segment an image into two regions: a floe and a background. It can be seen in Figure 5 that the proposed approach yields consistently more accurate results than the hierarchical step-wise optimization. For quantitative comparison between the methods we used the Dice score (Dice, 1945):

$$D = \frac{2|\hat{S} \cap S|}{|\hat{S}| + |S|}, \tag{10}$$

where $\hat{S}$ and S are manually and automatically segmented ice floe regions, respectively. It can be seen in Figure 6(a) that the hierarchical step-wise optimization is able to deliver good segmentations in several cases, but its effectiveness is inconsistent in a time series. The proposed method gives accurate results for all the images ($D > 0.92$ $\forall$ images), and yields consistently decreasing (with non-significant variations) melting ice profile, as shown in Figure 6(b).

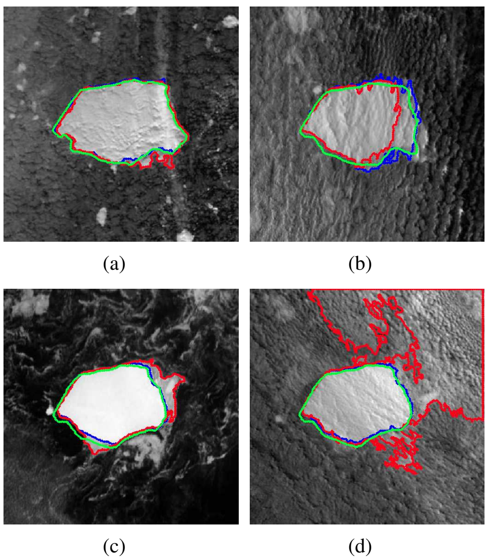


Figure 5: Comparison of results for images acquired on the 4th, 16th, 17th and 19th day, respectively. Manual segmentation ice floe contour is shown in green, hierarchical step-wise optimization result in red, and new graph-based approach in blue.

5 CONCLUSIONS

We have proposed a new method for segmentation of multiyear sea ice floes from time series of Aqua satellite images. The new graph-based approach performs best merge region growing, followed by the energy minimization on the image graph, where the energy consists of two terms describing the floe shape (shape term) and the gradient between the floe and the background (data term), respectively. We validated the performance of the proposed method for segmentation of a shrinking ice floe from a sequence of AMSR-E and MODIS images acquired in August-October 2008. The obtained results did show both the effectiveness of the proposed approach and its robustness to low-contrast data.

ACKNOWLEDGEMENTS

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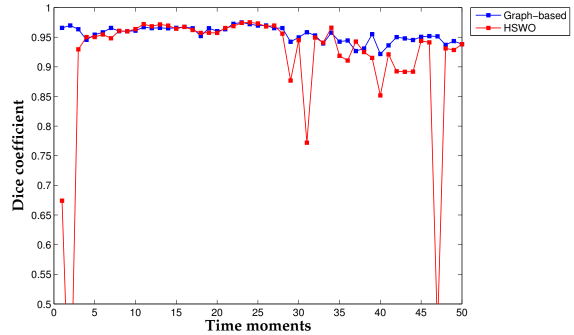
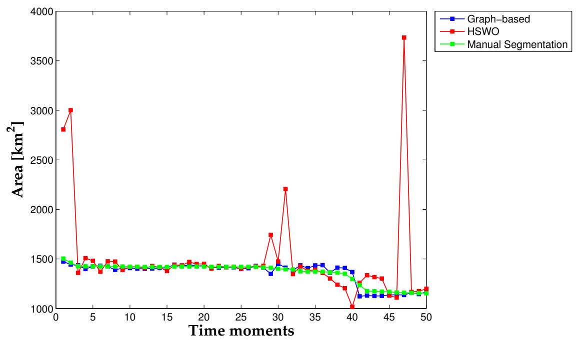


(a)



(b)

Figure 6: (a) Comparison of the performance of the proposed method versus hierarchical step-wise optimization (HSWO) technique in terms of the Dice score. (b) Area [km^2] of the segmented ice floe as a function of time.

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